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Poster P-???

Mean-field reduction of a layered macroscopic network model

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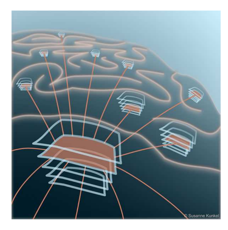

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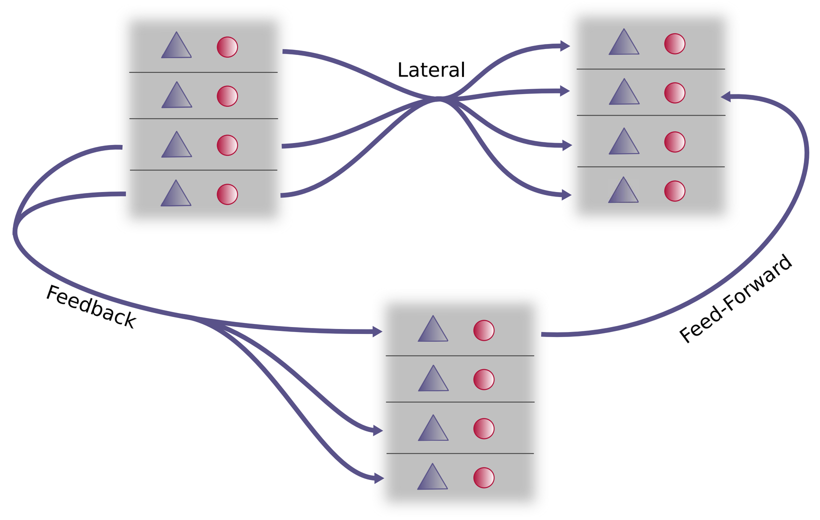
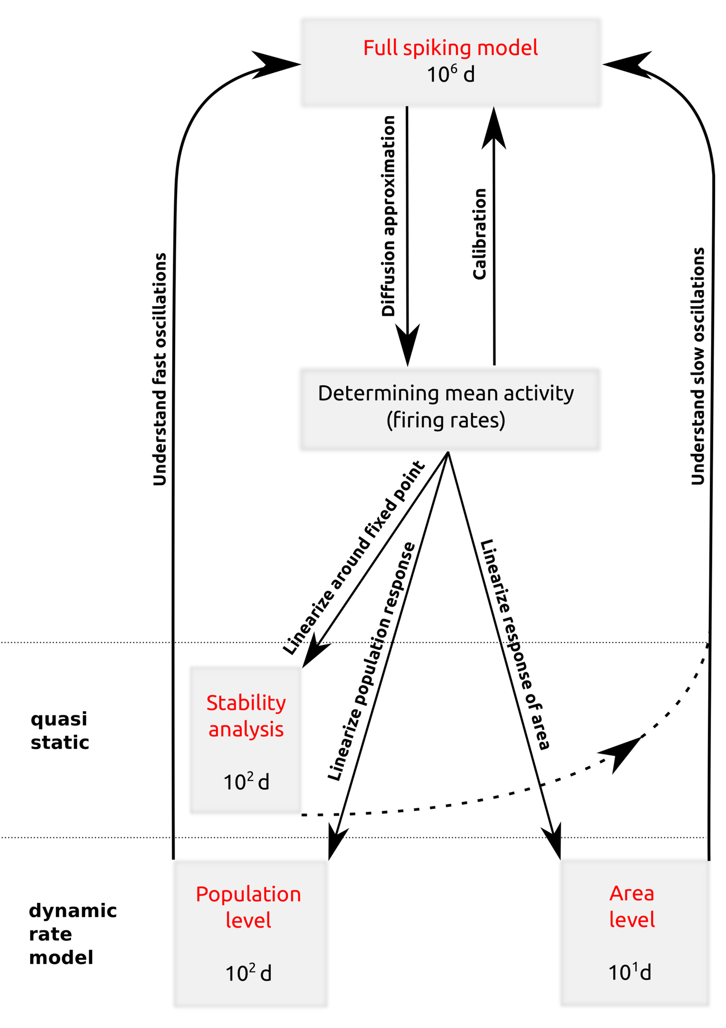
Motivation

- Understand mean activity and oscillations in a layered macroscopic model of the macaque visual cortex.
  Visit poster P-1: Integrating multi-scale data for a network model of macaque visual cortex
- Model details:
  - 32 visual areas modeled as single micro-columns
  - 254 neuron populations
  - currently $6 \cdot 10^6$ neurons, $1.2 \cdot 10^7$ dynamic variables
- **Goal: Understand the dynamics of this high dimensional system**
- **Method: Reduction of complexity**
  - coarser spatial description on the level of populations/areas
  - reduce temporal resolution, quasi static description





Mean population activity

- Neuron dynamics

$$\tau_m \frac{dV}{dt} = -V + I_s(t)$$
$$\tau_s \frac{dI_s}{dt} = -I_s + \tau_m \sum_{i=1}^{N} J_i \delta(t - t_i - d)$$

- Stochastic description of the neuronal input current:

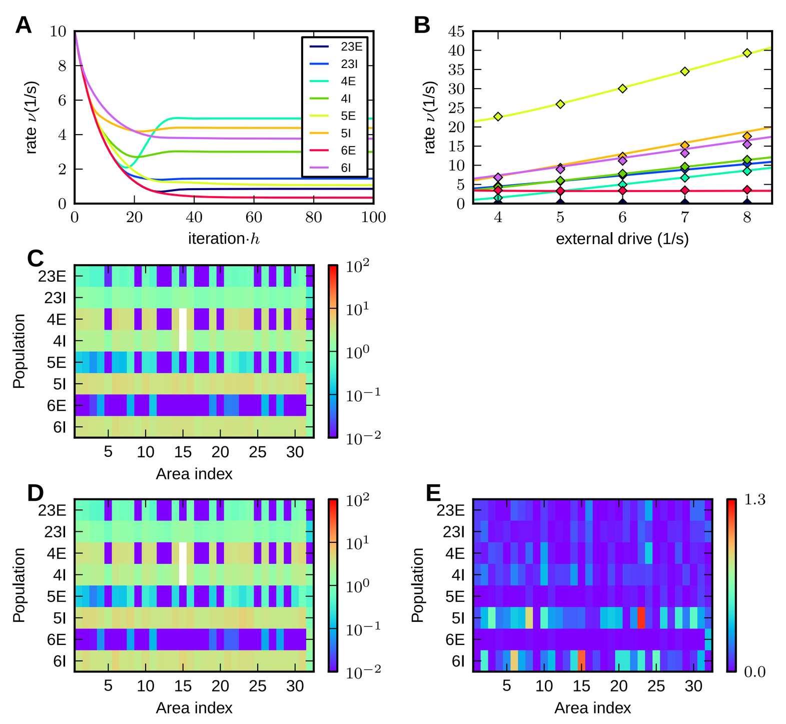
$$\tau_s \frac{dI_s}{dt} = -I_s + \mu + \sigma\sqrt{\tau_m}\eta(t)$$

- Self-consistent equation for stationary firing rates [2]:

$$\frac{1}{\nu_i} = \tau_r + \tau_m\sqrt{\pi}\int_{\frac{V_r-\mu_i}{\sigma_i}+\frac{\alpha}{2}\sqrt{\frac{\tau_s}{\tau_m}}}^{\frac{\Theta-\mu_i}{\sigma_i}+\frac{\alpha}{2}\sqrt{\frac{\tau_s}{\tau_m}}} e^{s^2}\left(1+\mathrm{erf}(s)\right)ds$$
$$\equiv \frac{1}{\Phi_i(\boldsymbol{\nu})}$$
$$\mu_i = \sum_j \tau_m (KJ)_{ij}\nu_j$$
$$\sigma_i = \sum_j \tau_m (KJ^2)_{ij}\nu_j$$

- Finding the fixed point by integrating first order quasi dynamics [6]:

$$\frac{d\boldsymbol{\nu}}{dt} = \boldsymbol{\Phi}(\boldsymbol{\nu}) - \boldsymbol{\nu} \qquad (1)$$



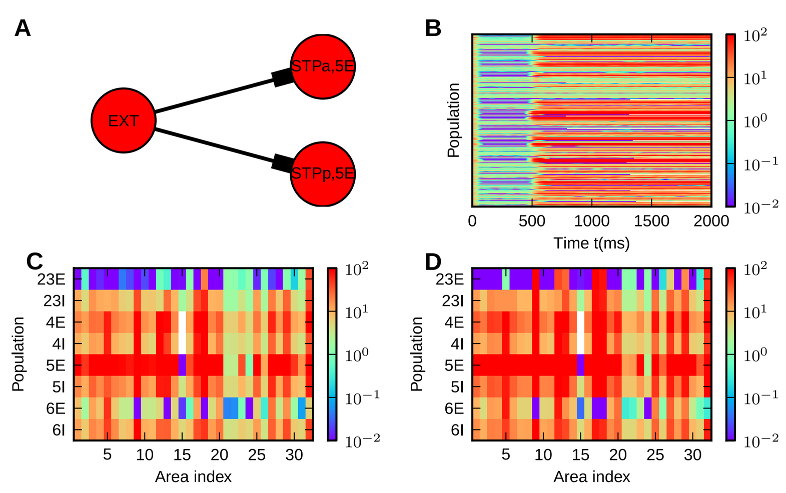
A Integration of (1) with timestep h
B Firing rates in different layers of isolated area V1 depending on the external drive
C Theoretical firing rates (fixed point solution) in all 32 areas
D Simulated firing rates corresponding to C
E Deviation $\Delta\nu$ between theory (C) and simulation (D)

Stability analysis

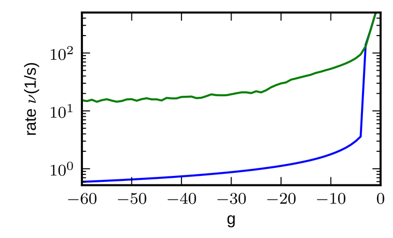
- Main model parameters: external drive and ratio g of inhibitory to excitatory weights
- Bistable system: stable low and high activity state for a large range of g
- Time Evolution of a small perturbation $\epsilon at quasi time t_p$:

$$\frac{d\boldsymbol{\epsilon}}{dt} = (\underbrace{-\mathbf{1} + \Phi'\mathbf{W}}_{\tilde{J}})\boldsymbol{\epsilon}$$

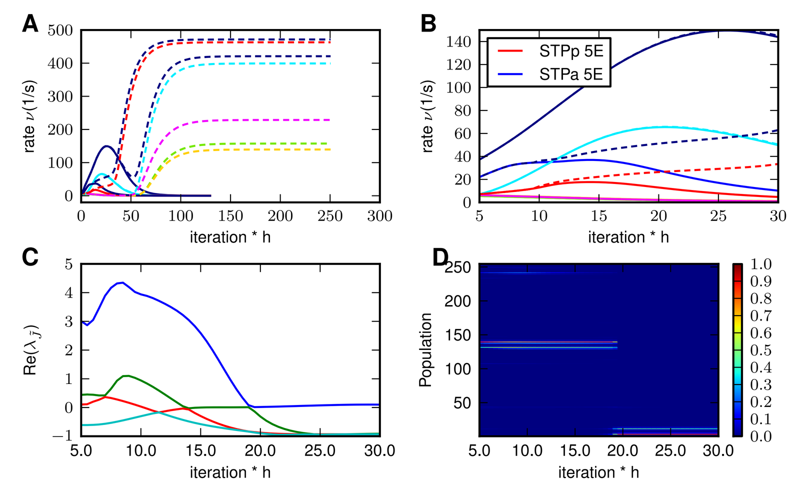
- Exponential growth if $\mathrm{Re}(\lambda_j) > 0$
- During transient phase the system is sensitive to a perturbation in the direction of the populations STPa,5E and STPp,5E
- External excitation of STPa,5E and STPp,5E in the spiking Simulation leads to a transition from the low to the high activity state
- In general the network can be stabilized by modifying the number of II-synapses in the layer 5 E-I subnetworks.
- After stabilization and increase of external input to excitatory populations, the network shows slow oscillating activity



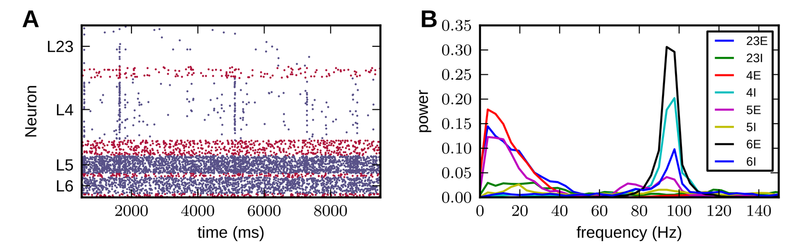
A Illustration of the external excitation of the spiking network
B Time evolution of firing rates encoded in color. External excitation applied at $t = 500ms$ for a duration of $300ms$
C Mean-field solution for high activity state
D Simulated mean firing rates after transition to the high activity state



Hysteresis curve for a variation of parameter g.
Blue line: Increase of g. Green line: Decrease of g.



A Solid line: Trajectory of firing rates for eight different populations, representative for all 254 populations. Dashed line: perturbed at $\mathrm{iteration} \cdot h = 10$ in direction of most unstable eigenvector
B Zoom of transient phase in A
C Four largest eigenvalues of $\tilde{J}$ during transient phase
D Time evolution of 254 dimensional eigenvector, corresponding to largest eigenvalue during transient phase. Absolute value of each component encoded in color.



A Raster plot for area V1, embedded in the whole network model
B Firing rate spectra for the eight different populations in V1, corresponding to A

Dynamical mean-field description

- Spiking model can be mapped to a linear rate model [3,4]

$$\mathbf{r}(t) = \mathbf{h}(\circ) * [\boldsymbol{w}(r(\circ - d) + \mathbf{x}(\circ))](t) \qquad (2)$$

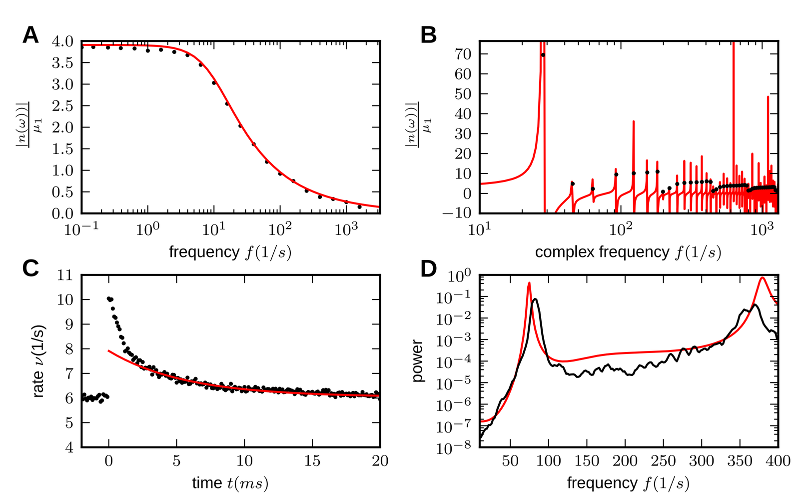
- Impulse response $\mathbf{h}(\circ)$ was derived analytically in frequency domain, i.e. $\tilde{H}(\omega)$ for δ-shaped currents
- Back transform via residue theorem reveals important time constants [5]

$$h(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} e^{i\omega t}\tilde{H}(\omega)d\omega$$
$$= \sum_{\omega_0} Res(\tilde{H}, \omega_0)e^{i\omega_0 t}\Theta(t)$$

- Population power- and cross spectra can be derived from (2)

$$\mathbf{C}(\omega) = \mathbf{P}(\omega)\mathbf{D}\mathbf{P}^T(\omega) \qquad (3)$$
$$\mathbf{P}(\omega) = (H_d^{-1}(\omega) - \mathbf{W})^{-1}\mathbf{W} + 1 \qquad (4)$$

- Significant peaks in power spectra of populations can be explained by considering only the most important time constant



A Red line: Transfer function in frequency domain. Black Dots: Simulation.
B Red line: Analytical continuation of transfer function over purely imaginary frequency axis. Black dots: value of $Res(\tilde{H}, \omega_0)$ at purely imaginary poles ω_0 (same y-axis).
C Black dots: Firing rate response from simulation (dots) approximated by largest residue and corresponding pole/time constant.
D Black line: Power spectrum for population 4I in isolated area 'V1'. Black line: Simulation. Red line: Analytical prediction (3) using transfer function approximated as in C.

References

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Outlook

- Slow oscillations can emerge in spiking neural networks in the meta-stable regime due to rate instabilities [1]
- Identify mechanisms and recurrent loops controlling fast and slow oscillations via dynamical mean-field description and stability analysis
- Study emergence of slow oscillations by reducing singe areas to input-output relationships (area transfer function)
- Extraction of macroscopic signal (BOLD) from the model for comparison to empirically observed slow oscillations, i.e. resting state activity
- Comparison of functional connectivity maps between model and experiment

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